EMG-based Gesture Recognition

Marina Georgoula

University of Patras
Department Of Electrical & Computer Engineering

Abstract

This MSc. Thesis is dealing with the study and implementation of pretrained Convolutional Neural Networks and their performance on hand movement classification, using surface EMG signals. The sEMG signal is recorded by surface electrodes, whose number varies depending on the database. Three public databases are used in this thesis, each containing data recorded by different number of sensors: DB1 NinaPro (10 electrodes) [1] , DB5 NinaPro (16 electrodes) [2], DBc CapgMyo (128 electrodes) [3].
The data of 12 finger movements is preprocessed and separated by applying sliding windows to create a three-channel sEMG image. The window size is experimentally set and determines the size of the image [4].
As a first step, each pretrained model, originally trained on ImageNet, is taking a sEMG image as input, and implements Transfer Learning [5] in order to adjust the model's parameters to the EMG data. The pretrained models used in this thesis are VGG16, VGG19 [6], ResNet50 [7], InceptionV3 [8].
As a second step of the experimental procedure, the best performing pretrained models for each database are used to examine the number and position of the electrodes [9].

Methods used

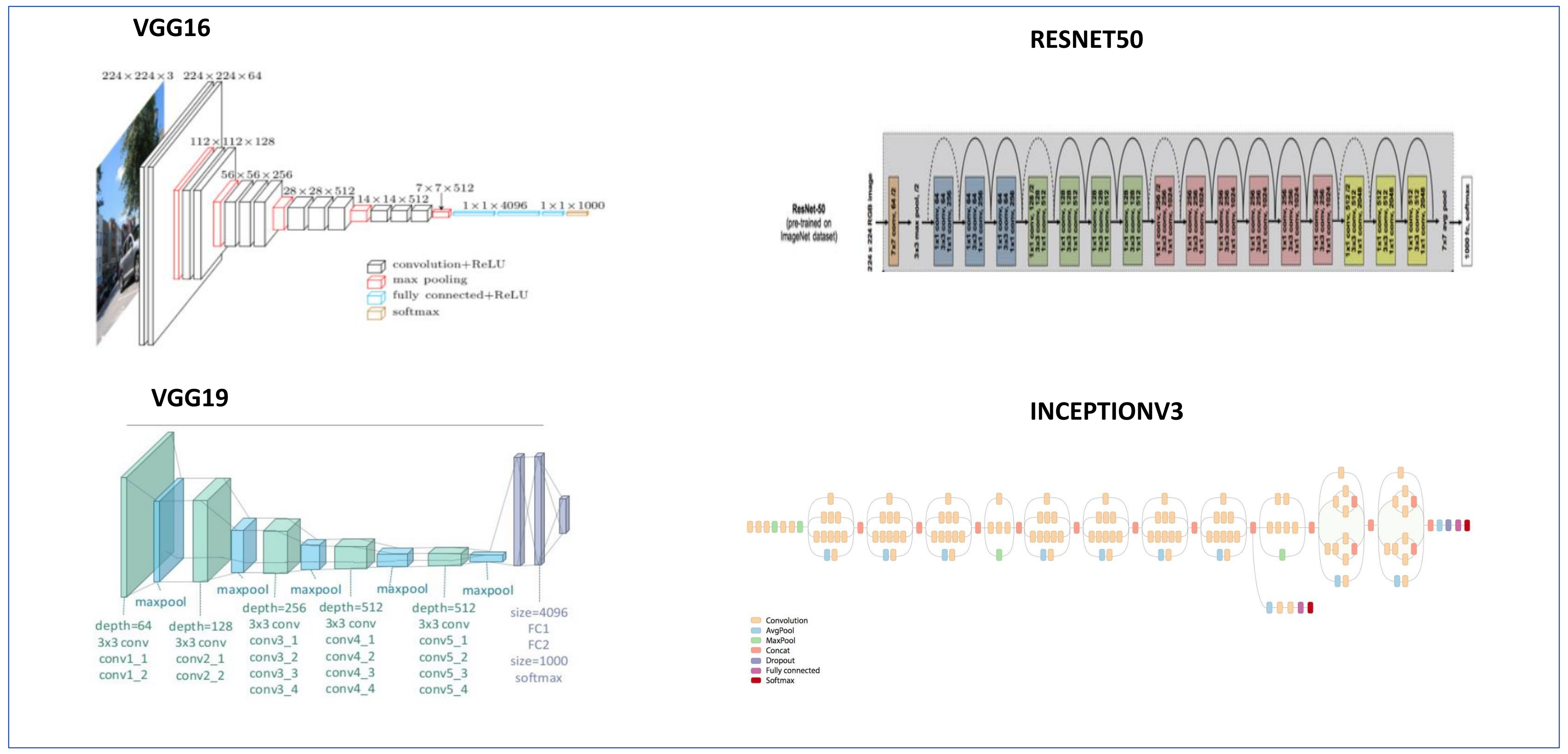
For Part A, the training of the networks is separated in two stages:

- Fine Tuning: Freeze the weights of the first layers of networks which capture universal features such as curves and edges and train with small learning rate
- Training: Freeze all layers of the original model and train only the classifier avoiding overfitting

For Part B, the electrodes are examined by:

- Zeroing the electrode
- Replacing the electrode with random noise

Pretrained Convolutional Neural Networks used



Experimental Procedure

Part A - Fine Tuning

Modify pretrained models → Add new classification layers → Freeze only first layers → Train for a few epochs

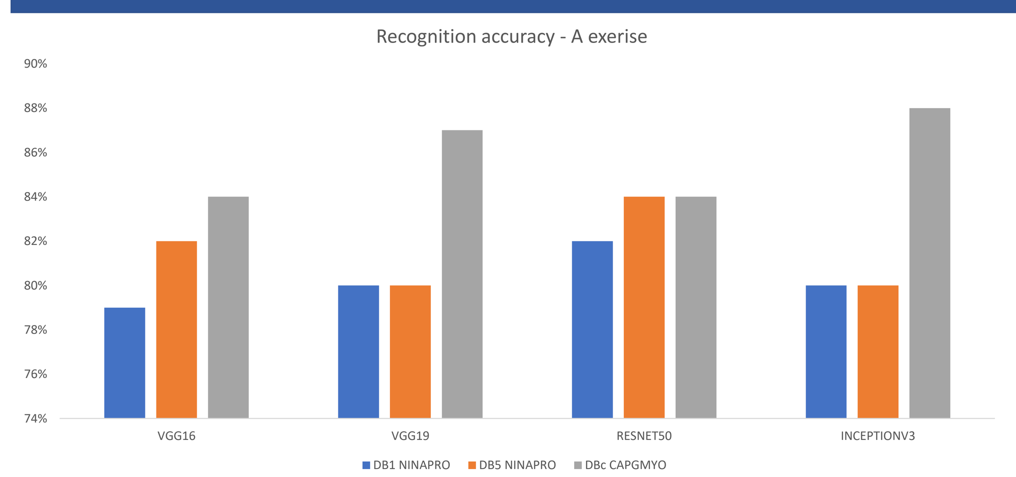
Part A –Training

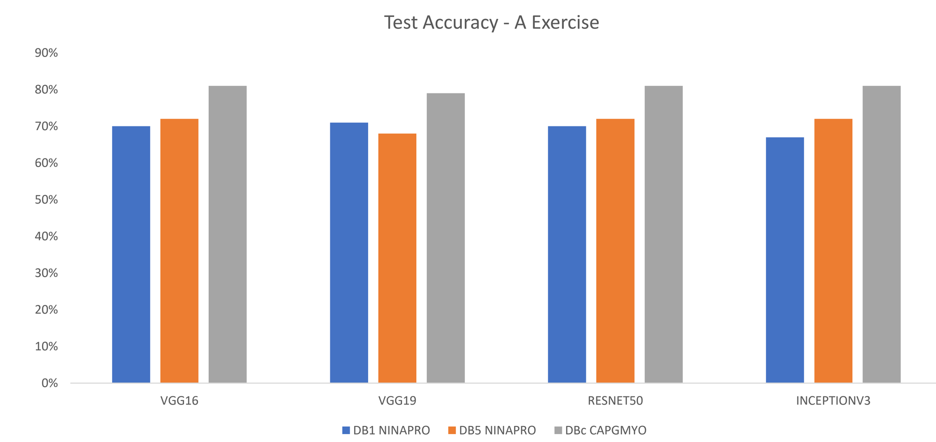
Freeze all pretrained model's layers → Train only classifier → Adjust parameters → Select best performing model of each category

Part B – Examine electrodes

Best performing models for each database → Zero electrode → Replace electrode with random noise → Compare results

Results – Part A





Results – Part B

DB1 NinaPro	Electrodes	Test Accuracy	Test Loss
Most active	7, 8	26 – 30 %	3.99 – 6.07
Less active	3, 4, 5	50 – 67 %	≈856

DB5 NinaPro	Electrodes	Test Accuracy	Test Loss
Most active	9, 10	24 – 37 %	2.66 – 5.75
Less active	3, 4, 5, 11, 12, 13	46 – 62 %	1.30 – 3.12

DBc CapgMyo	Electrodes	Test Accuracy	Test Loss
Most active	[17:32], [65:80]	14 – 38 %	2.92 – 5.91
Less active	[97:112], [113:128]	52 – 66 %	1.35 – 2.09

Conclusions

Overall, regarding the results of Part A, the best classified database is DBc CapgMyo, possibly due to its high-density EMG data recorded from 128 sensors. Among the four pretrained CNN models, the best performing model is ResNet50 in all three databases achieving an average training accuracy of 83,3% and an average testing accuracy of 74,3%.
For the second part of the experimental procedure, the results of both techniques are compared with each other and with the ground truth of the electrodes activation for each gesture. The most active electrodes are considered to result in very low prediction accuracy when zeroed or replaced, and the less active electrodes are the ones to achieve high prediction accuracy despite their distortion. As far as their positioning in concerned, according to the databases makers, the electrodes where randomly and symmetrically positioned around the forearm.

Future Directions

- Redesign pretrained model's classification layers for better performance
- Augment data by adding all hand movements from databases
- Implement Transfer Learning for more pretrained models, such as Xception, InceptionV3, ResNeXt.

Contact Information

Marina Georgoula
marinageo19941@gmail.com

References

1. Atzori, Manfredo & Gijsberts, Arjan & Castellini, Claudio & Caputo, Barbara & Mittaz Hager, Anne-Gabrielle & Elsig, Simone & Giatsidis, Giorgio & Bassetto, Franco & Müller, Henning. (2014). Electromyography data for non-invasive naturally-controlled Robotic hand prostheses. Nature. 1. 10.1038/sdata.2014.53.
2. Pizzolato S, Tagliapietra L, Cognolato M, Reggiani M, Müller H, Atzori M (2017) Comparison of six electromyography acquisition setups on hand movement classification tasks. PLoS ONE 12(10): e0186132.
3. Geng, W., Du, Y., Jin, W., Wei, W., Hu, Y., and Li, J.(2016). Gesture recognition by instantaneous surface EMG images. Scientific Reports, 6(36571)
4. Tsinganos, P & Cornelis, Bruno & Cornelis, Jan & Jansen, Bart & Skodras, Athanassios. (2019). Deep Learning in EMG-based Gesture Recognition
5. Hussain, Mahbub & Bird, Jordan & Faria, Diego. (2018). A Study on CNN Transfer Learning for Image Classification.
6. Gopalakrishnan, K., Khaitan, S. K., Choudhary, A. N., & Agrawal, A. (2017). Deep Convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection. Construction and Building Materials, 157, 322-330.
7. Ji, Qingge & Huang, Jie & He, Wenjie & Sun, Yankui. (2019). Optimized Deep Convolutional Neural Networks for Identification of Macular Diseases from Optical Coherence Tomography Images. Algorithms. 12. 51. 10.3390/a12030051
8. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)
9. De Luca, C.J. (2002) Surface Electromyography: Detection and Recording. DelSys Incorporated, 2-10.